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ONR - Technical Report 88-1

A Componential Analysis of Cognitive Effort in Choice

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September, 1988

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Sponsored by:
Perceptual Sciences Programs
Office of Naval Research
Contract Number N00014-80-C-00114

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In Press:
Organizational Behavior and Human Decision Processes

88 9

SECURITY CLASSIFICATION OF THIS PAGE

ADA199587

REPORT DOCUMENTATION PAGE

1a. REPORT SECURITY CLASSIFICATION UNCLASSIFIED	1b. RESTRICTIVE MARKINGS
2a. SECURITY CLASSIFICATION AUTHORITY	3. DISTRIBUTION / AVAILABILITY OF REPORT APPROVED FOR PUBLIC RELEASE: DISTRIBUTION UNLIMITED
2b. DECLASSIFICATION / DOWNGRADING SCHEDULE	
4. PERFORMING ORGANIZATION REPORT NUMBER(S) ONR Tech Report 88-1	5. MONITORING ORGANIZATION REPORT NUMBER(S) N/A
6a. NAME OF PERFORMING ORGANIZATION Duke University 6b. OFFICE SYMBOL (If applicable)	7a. NAME OF MONITORING ORGANIZATION Office of Naval Research
6c. ADDRESS (City, State, and ZIP Code) Fuqua School of Business Duke University Durham, NC 27706	7b. ADDRESS (City, State, and ZIP Code) Arlington, VA 22217-5000
8a. NAME OF FUNDING / SPONSORING ORGANIZATION Office of Naval Research 8b. OFFICE SYMBOL (If applicable) Code 1142PS	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER Contract N00014-80-C-0114
8c. ADDRESS (City, State, and ZIP Code) Arlington, VA 22217-5000	10. SOURCE OF FUNDING NUMBERS PROGRAM ELEMENT NO: 61153N PROJECT NO: RR-042-09 TASK NO: 4425 WORK UNIT ACCESSION NO: R&T 4425063

11. TITLE (Include Security Classification)

A Componential Analysis of Cognitive Effort in Choice

12. PERSONAL AUTHOR(S)

Bettman, J.R., Johnson, E.J., & Payne, J.W.

13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
Research	FROM _____ TO _____	September, 1988	#

16. SUPPLEMENTARY NOTATION

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

A model for measuring the cognitive effort required to execute a decision strategy is proposed. The model is based on a set of elementary information processes (EIP's), (e.g., reads, comparisons, additions) that are assumed to be common components of decision strategies. A weighted sum of EIP's model is shown to provide good predictions for response time and subjective reports of effort. Estimates of the time and effort associated with each EIP seem plausible and consistent with those found in other cognitive tasks. Overall, the EIP approach to conceptualizing and measuring the effort of executing a choice strategy receives strong support.

20. DISTRIBUTION / AVAILABILITY OF ABSTRACT ☒ UNCLASSIFIED/UNLIMITED ☐ SAME AS RPT ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION UNCLASSIFIED
22a. NAME OF RESPONSIBLE INDIVIDUAL GERALD S. MALECKI	22b. TELEPHONE (Include Area Code) (202) 696-4741 22c. OFFICE SYMBOL Code 1142PS

DD FORM 1473, 84 MAR — 83 APR edition may be used until exhausted. All other editions are obsolete.

SECURITY CLASSIFICATION OF THIS PAGE

A major finding of the last decade of decision research is that an individual may use many different kinds of strategies in making a decision, contingent upon task demands (Payne, 1982; Abelson & Levi, 1985). The use of multiple strategies raises the fundamental issue of how people decide what to do. An approach advocated by many researchers is to look at various decision strategies as having differing advantages and disadvantages, and to hypothesize that an individual might select the strategy that is, in some sense, best for the task. Several factors, such as the chance of making an error, justifiability (Tversky, 1972), and the avoidance of conflict (Hogarth, 1987), can play an important role in strategy selection. However, in the current paper we focus on another factor that is generally assumed to exert a major influence on strategy use, the effort (cognitive resources) required to perform a strategy (Beach & Mitchell, 1978; Johnson & Payne, 1985; Paquette & Kida, 1988; Russo & Dosher, 1983; Wright, 1975).

The notion that different decision strategies require different amounts of computational effort to execute seems obvious. The strategy of expected utility maximization, for instance, requires a person to process all relevant problem information and to trade off values and beliefs. The lexicographic choice rule (Tversky, 1969), on the other hand, chooses the alternative which is best on the most important attribute, ignoring much of the potentially relevant problem information. Thus, there appear to be clear differences among decision strategies in the amount of information that is processed in making a choice.

At a more precise level of analysis, however, a comparison among decision strategies in terms of cognitive effort is much more difficult. In part this is because the decision strategies that have been proposed in the literature have varied widely in terms of their formal expression. Some have been proposed as formal mathematical models (e.g., elimination-by-aspects, Tversky, 1972), and

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others as verbal process descriptions (e.g., the majority of confirming dimensions rule, Russo & Dosher, 1983). What is needed is a language that could be used to express a diverse set of decision strategies in terms of a common set of cognitive operations. Such a language would provide a unifying framework for describing strategies and allow strategy selection to be investigated at an information processing level rather than at a more general level of analysis, such as analytic vs. nonanalytic (Beach and Mitchell, 1978) or analytic vs. intuitive (Hammond, 1986). Such a language would also allow a more detailed analysis of the components of processing (effort) involved when a particular decision strategy is used to solve a particular decision problem (Maule, 1985). In other words, one could examine whether the amount of information to be processed is the major determinant of effort, or whether the specific mix of cognitive operations which is utilized affects effort.

In addition to the problem of conceptualizing effort, another difficulty is actually measuring the effort associated with a given strategy. There have been a number of measurement techniques proposed for the related concept of mental workload (Gopher & Donchin, in press; Wickens, 1984), ranging from self-reports to response times to physiological measures. However, the different measures of workload, such as response latencies, secondary tasks, or self-reports, do not always agree. Hence, Gopher and Donchin (in press) recommend the use of multiple measures, along with a detailed theoretical analysis of the expected workload of a task.

The purposes of this paper are 1) to conceptualize and develop a metric for modeling decision effort; 2) to characterize the effort put forth by subjects using different decision strategies in different choice environments; and 3) to assess the degree to which the proposed model is able to fit the subjects' effort. To accomplish these goals, we first develop a metric of decision effort

based on the concept of elementary information processes (Chase, 1978; Newell & Simon, 1972). We then examine the effort required by subjects to use different decision strategies in choice environments varying in complexity, using two indicators of strategy execution effort: decision latencies and self-reports of task difficulty. We then use the proposed elementary information processes (EIP) approach to modeling decision effort to predict these two indicators of strategy execution effort. Our overall goal is not to propose a complete theory of mental workload, but rather to illustrate an approach to measuring the execution effort of choice strategies.

In the following section, previous attempts to conceptualize and measure decision effort are briefly addressed, and the proposed approach is outlined. Then the methodology and results of a study designed to test this approach are described in detail.

Measuring Decision Effort

The theoretical construct of mental effort has a long and venerable history in psychology (Kahneman, 1973; Navon & Gopher, 1979; Thomas, 1983). However, there have been only a few attempts to model and compare decision rules in terms of an effort metric.

Two studies that attempted to directly measure the execution effort of various decision rules are Wright (1975) and Bettman & Zins (1979). In each study, subjects were instructed to use particular decision rules to solve certain problems. The percent of correct judgments using the rules and self-reports of task difficulty or ease of use were obtained in both studies. In addition, Bettman and Zins obtained a measure of the time taken to apply a rule to a problem. The results clearly show that the rules were perceived to differ in the effort required. For example, a lexicographic rule was generally perceived as less effortful than other decision rules. That rule also tended to be the most

accurate and quickest in its execution. However, these two studies had significant limitations. First, neither study employed a method beyond initial instruction to ensure that subjects actually used the prescribed decision rules. Second, neither study provided a conceptual basis (model) for why a certain decision rule would be expected to be more or less effortful in a particular task. That is, neither study attempted to model the components of decision-making effort.

Shugan (1980) suggested an effort metric based upon one operation, the binary comparison of two alternatives on an attribute. More effortful decisions involved more comparisons. Shugan also showed that the effort of strategies would vary with certain task characteristics like the correlational structure among attributes. Unfortunately, using the binary comparison as the fundamental unit of effort restricts Shugan's analysis to certain decision rules. Nonetheless, Shugan's work implies that any approach to modeling strategy effort must be sensitive to the joint effects of strategy and task.

Based upon the work of Newell and Simon (1972), Huber (1980) and Johnson (1979) offered decompositions of choice strategies using more extensive sets of components. Each independently suggested that decision strategies be described by a set of elementary information processes (EIPs). A decision rule or strategy was represented as a sequence of mental events, such as reading a piece of information into STM (short-term memory), multiplying a probability and a payoff, or comparing the values of two alternatives on an attribute. Johnson and Payne (1985) and Payne, Bettman, and Johnson (In press) employed a similar set of EIPs for decision making, shown in Table 1, and constructed production system implementations of several different choice strategies.

A particular set of EIPs, like the one given above, represents a theoretical judgment regarding the appropriate level of decomposition for

decision processes. For instance, the product operator might itself be decomposed into more elementary processes. We hypothesize, however, that the above level of decomposition provides the basis for meaningful comparisons among decision strategies in terms of effort. Furthermore, we propose that a general measure of decision effort is the number of component EIPs required to execute a particular strategy in a particular task environment. This notion of measuring decision effort in terms of the number of EIPs builds on an idea for measuring processing effort proposed by Newell and Simon (1972). Empirical support for this approach in areas other than decision making has been provided by showing a relationship between the predicted number of EIPs used and response times for a variety of cognitive tasks (Card, Moran, & Newell, 1983; Carpenter & Just, 1975).

Table 1

Elementary EIP's Used in Decision Strategies

READ	Read an alternative's value on an attribute into STM
COMPARE	Compare two alternatives on an attribute
DIFFERENCE	Calculate the size of the difference of two alternatives for an attribute
ADD	Add the values of an attribute in STM
PRODUCT	Weight one value by another (Multiply)
ELIMINATE	Remove an alternative or attribute from consideration
MOVE	Go to next element of external environment
CHOOSE	Announce preferred alternative and stop process

To validate this componential (EIP) approach to measuring choice effort, we examine four models of decision effort based upon EIPs. The simplest model of decision effort using EIPs would be to treat each component process as equally effortful and simply sum the numbers of each component process to get an overall measure of effort (the equal-weighted EIP model). A second and slightly more complex model would allow the effort required by each individual component to vary (the weighted EIP model). Total effort would then be a weighted sum of the individual operations. A third model would allow the effortfulness of the individual EIPs to vary across rules (the weighted EIP by rule model). While such variation is of course a possibility, one would hope that the effortfulness of an EIP would not vary as a function of the particular strategy of which it is a component. The goal of developing a unifying framework for describing different decision strategies would be more difficult to attain if the sequence of operations or the rule used affected the effort required for an EIP. Finally, the fourth model would allow the required effort for each EIP to vary across individuals (the weighted EIP by individual model). One might expect that some individuals might find certain EIPs (e.g., the PRODUCT operator) relatively more difficult than other individuals, for example.

An alternative model of effort which is not based on the componential approach is also considered. This model is based on the number of items of information processed by a particular strategy in a choice environment. Since it is easy to monitor information acquisition behavior, this might be called an explicit behavioral model of strategy effort. A model based solely on information acquisition implies that the specific type of processing done on the information acquired makes little or no difference in determining decision effort. Such a model represents a base-line model of effort in that the details of processing are ignored.

These models of strategy effort are investigated with data from subjects using different rules across choice tasks varying in complexity (number of alternatives and attributes). The performance of the subjects on the various rules in the different tasks is characterized by two indicators of execution effort: the time to make a response and self-reports of effort. We then use the models proposed above to predict these two indicators. The details of the methodology used are presented next.

Method

Overview

Subjects were trained to use six different strategies for making decisions. Each strategy was used in a separate session to make twenty decisions for decision problems ranging in size from two to six alternatives and from two to four attributes. Subjects used a computer-based information acquisition system to acquire information and make decisions among sets of alternatives (Johnson, Payne, Schkade, & Bettman, 1986). The computer-based acquisition system monitored the subjects' information sequences; recorded latencies for each acquisition; recorded the overall time for each problem; and recorded any errors made by the subject (i.e., departures from the prescribed search pattern or choice). In addition, subjects rated the difficulty of each choice and the effort each required on two response scales presented at the end of each decision problem. Subjects also provided data in a seventh session for twelve choice problems of various sizes where the subject was free to use any strategy desired. Some suggestive findings from these data are considered in the discussion section.

We describe the details of the methodology for the prescribed strategy sessions as follows: first, the six decision strategies used are described, followed by a description and examples of how the EIP counts were generated.

Then the generation of the sets of twenty decision problems is discussed, followed by details on the computer-based acquisition system. The experimental procedure is then discussed in detail and some preliminary analyses are reported. Finally, the details of the proposed models and an overview of the major analyses performed are presented.

Decision Strategies

Rules Used. Six different decision strategies were used in the prescribed strategy portion of the experiment: weighted additive; equal weighted additive; lexicographic; elimination by aspects; satisficing (conjunctive); and majority of confirming dimensions. Each of these rules was implemented as a production system model (for examples see Johnson and Payne, 1985; Payne, Bettman, and Johnson, In press). These particular rules were selected for two reasons: 1) each rule has been a focus of previous research on choice processes; and 2) this set of rules provides a broad coverage of the set of basic elementary operations (EIPs) used as the components in our conceptualization of strategy execution effort. We first describe the strategies, and then the elementary operations are considered.

A typical choice problem in our study consists of a set of alternative job candidates, each of whom is described by scores, or ratings, on various selection attributes or criteria (e.g., leadership potential and motivation). For each attribu e, an importance weight and a cutoff value specifying a minimally acceptable level for that attribute were also displayed. Different decision strategies might use both weights and cutoffs, one of the two, or neither, as described below.

The weighted additive (WADD) rule requires the subject to develop an evaluation for each alternative by multiplying each weight times the attribute rating and adding those products for all attributes. The alternative with the

highest evaluation is selected. In the equal weighted additive (EQW) model, the evaluation for each alternative is obtained by adding the ratings for all the attributes, with the alternative with the highest evaluation selected. No weights or cutoffs are used.

The lexicographic (LEX) rule requires the subject to first find the most important attribute (the attribute with the largest weight) and then search the values on that attribute for the alternative with the highest value. That alternative is selected, unless there are ties. In this case, those tied alternatives are examined on the second most important attribute. That process continues until a winner is found.

The elimination by aspects (EBA) strategy also begins by determining the most important attribute and examining that attribute's cutoff value. Next, all alternatives with ratings below the cutoff for that attribute are eliminated. This process continues with the second most important attribute, and so on, until one alternative remains. The satisficing (conjunctive) (SAT) rule requires the subject to consider one alternative at a time, comparing each attribute to the cutoff value. If any attribute is below the cutoff value, that alternative is rejected. The first alternative which has values which pass the cutoffs for all attributes is chosen.

Finally, the majority of confirming dimensions rule (MCD) processes pairs of alternatives. The values of the two alternatives are compared for each attribute, and a running score is kept: if the first alternative has a greater value on an attribute than the second, one is added to the score; if the second alternative is greater, one is subtracted; if the two alternatives are tied, the score is not changed. After all attributes have been examined, if the score is positive, the first alternative is retained; if the score is negative, the second alternative is retained; and if the score is zero, the alternative winning the

comparison on the last attribute is retained. Thus, the general idea is to retain the alternative which is better on the most criteria. The alternative which is retained is then compared to the next alternative remaining among the set of alternatives. If no other alternative remains, the retained alternative is selected.

Calculating EIP Counts

To describe the steps a subject followed in more detail and to show how EIP counts were determined, we first consider the particular EIPs used and then present two more detailed examples of rules applied to a particular decision problem. The major EIPs utilized were MOVES, READS, ADDITIONS, PRODUCTS, COMPARES, ELIMINATIONS, and DIFFERENCES. A MOVE involves moving to another piece of information, while a READ consists of acquiring that information (moving it to short term memory). Since MOVES and READS are perfectly correlated in our experiment, we will only consider READS (acquisitions) in this study. ADDITIONS, PRODUCTS (of weights and ratings), and DIFFERENCES are self-evident. COMPARES involved comparing two pieces of information and determining the larger (two ratings, two overall alternative scores, two weights, a rating and cutoff, etc.). Finally, ELIMINATIONS could be either discarding an attribute (because it had already been used) or an alternative (because its score was surpassed, it failed a cutoff, etc.).

Examples. Two examples will be considered in more detail, a weighted adding case and an EBA example. Before doing this, however, some general comments are in order. First, the number of EIPs required for a particular decision is a function of the specific rule used, the size of the problem (the number of alternatives and attributes), and the specific values of the data. Rules which examine all of the ratings for each alternative, such as the weighted adding rule, need more EIPs than rules which may process only part of the data,

such as the EBA rule. Larger problems also tend to require more EIPs. Problems with more values which surpass cutoffs will also generally require more EIPs. Second, in the specification of the rules, an attempt was made to take advantage of the left to right, top to bottom natural reading order.

Table 2
(a)

Example of a Four Alternative, Three Attribute Decision Problem

		Attributes		
Alternatives		Leadership	Creativity	Experience
	Weights	6(1)	4(2)	2(3)
A		4(4)	7(5)	4(6)
B		2(7)	7(8)	2(9)
C		6(10)	6(11)	3(12)
D		5(13)	7(14)	2(15)

(b)

Example of a Three Alternative, Four Attribute Decision Problem

		Attributes			
Alternatives		Leadership	Motivation	Creativity	Experience
	Weights	4(1)	5(2)	3(3)	6(4)
	Cutoffs	7(5)	4(6)	6(7)	6(8)
A		6(9)	5(10)	7(11)	7(12)
B		7(13)	4(14)	3(15)	6(16)
C		4(17)	3(18)	4(19)	4(20)

For the weighted adding rule, consider the 4 alternative, 3 attribute decision problem shown in Table 2a. The numbers in parentheses are labels that will be used for convenience for identifying the sequence of acquisitions in the following. Subjects were instructed to acquire the first weight (1) and then the rating on the first attribute (4). They then multiplied these two numbers and retained the score. This process was repeated (sequence (2), (5), (3), (6)) until alternative A was finished. For the first alternative, the total score of 60 was simply retained as the current best. After processing the first alternative, there would be six READS, three PRODUCTS, two ADDS, and no COMPARISONS, DIFFERENCES, or ELIMINATIONS. For alternative B, the sequence would be (1), (7), (2), (8), (3), (9). Then the total score for B, 44, would be compared to the current best, and the current best of 60 would be retained. The assumption was made that in the comparison of total scores, the losing alternative was not explicitly eliminated. Rather, the subject would merely store the one retained. Thus, after two alternatives we would have twelve READS, six PRODUCTS, four ADDS, one COMPARISON, no DIFFERENCES, and no ELIMINATIONS. This process would be repeated for the remaining two alternatives (sequence (1), (10), (2), (11), (3), (12), (1), (13), (2), (14), (3), (15)). Hence, the production system model predicts that in total this problem would require 24 READS, 8 ADDITIONS, 12 PRODUCTS, 3 COMPARISONS, no DIFFERENCES, and no ELIMINATIONS.

The example of a three alternative, four attribute problem shown in Table 2b is used to clarify the EBA rule specification. The subject had to first find the most important attribute. This was done by starting with the first weight and comparing it to the second, retaining the larger (the second). The second was then compared to the third, and the second was retained. Then the second was compared to the fourth, and the fourth (experience) was retained as the most

important attribute. The sequence of acquisitions would thus be (1), (2), (3), (4). There would be four READS and three COMPARISONS. Then the subject acquired the cutoff for experience and examined the value for all alternatives on experience, comparing each value to the cutoff and eliminating any alternative not passing the cutoff. In this case, the sequence would be (8), (12), (16), and (20), with alternative C eliminated. The total EIPs thus far would be eight READS, six COMPARISONS, and one ELIMINATION. Then the experience attribute would be eliminated, and the weights for the remaining three criteria would be acquired and compared, resulting in motivation's being selected as the second most important attribute (sequence (1), (2), (3)). Then the cutoff for motivation was acquired and the values for the retained alternatives, A and B, were compared to the cutoff (sequence (6), (10), (14)). At this point, there would be a total of 14 READS, 10 COMPARISONS, and two ELIMINATIONS. Both A and B passed the cutoff, so the subject would then eliminate the motivation attribute and return to the weights to determine the third most important remaining attribute, leadership (sequence (1), (3)). Then the cutoff for leadership was examined, A and B were compared to the cutoff, and A was eliminated. B would then be chosen (sequence (5), (9), (13). In total, there would be 19 READS, 13 COMPARISONS, and four ELIMINATIONS (two attributes and two alternatives).

These examples illustrate two principles: the number of EIPs varies with problem size and with the particular values used, and different rules use different subsets of the EIPs. With regard to the second point, the weighted adding rule uses READS, ADDITIONS, PRODUCTS, and COMPARISONS; the equal weighted adding rule uses READS, ADDITIONS, and COMPARISONS; the lexicographic rule uses READS, COMPARISONS, and ELIMINATIONS; the EBA rule uses READS, COMPARISONS, and ELIMINATIONS; the satisficing rule uses READS, COMPARISONS, and ELIMINATIONS; and the MCD rule uses READS, ADDITIONS, COMPARISONS, ELIMINATIONS, and DIFFERENCES.

It should also be noted that certain rules (weighted adding, equal weighted adding) have the same EIP counts for any problems of the same size (i.e., with the same number of alternatives and attributes). On the other hand, the other rules (lexicographic, EBA, satisficing, and MCD) can have different EIP counts even for problems of the same size, depending upon the particular values of the data. This property of the rules affected the selection of decision problems for the experiment, as discussed next.

Selection of the Decision Problems

As noted above, subjects completed twenty decision problems for each of the six decision rules. These decision problems were generated by taking several factors into account. First, pilot studies revealed that problems with more than four attributes were extremely difficult for subjects, particularly for the weighted adding rule. Second, problems with more than six alternatives caused crowding on the computer display used in the information acquisition system. Hence, the decision problems varied from two to six alternatives and two to four attributes. This generated 15 possible sizes, ranging from two alternatives and two attributes to six alternatives and four attributes.

For the weighted adding and equal-weighted adding rules, since problem size determines the EIP count, one problem of each size was included, making fifteen decision problems. Then five problem sizes were randomly selected to complete the twenty decision problems. Values for the weights and ratings were assigned randomly, with the restriction that no overall scores for alternatives in the same problem set were tied.

For the remaining rules, several problems were generated for each problem size that represented low, intermediate and high EIP counts for that size (e.g., for a three alternative, four attribute EBA problem, elimination of two alternatives on the first attribute would lead to a low count, retention of all

three alternatives until the last attribute would be a high count, and the operations used for the example described above might be an intermediate count). Then sets of twenty problems were randomly selected for each rule from the total set of forty-five size/count combinations. Note that this selection procedure implies that for each rule other than weighted adding and equal-weighted adding there may be some problem sizes which were not selected.

The random selection procedure just described was repeated many times in an attempt to deal with correlation problems among the EIP counts. Since the EIP counts were to be used as independent variables in regression models to predict decision times and self reports of effort, it was desirable that their intercorrelations across all 120 decision problems should be as low as possible to avoid multi-collinearity problems (Kmenta 1986). As noted above, however, certain rules use only some EIPs and not others, so there are some correlations that will be high because of the definition of the rules. For example, the correlation between COMPARISONS and ELIMINATIONS will tend to be high because rules with no ELIMINATIONS (e.g., the adding rules) tend to do very few COMPARISONS, whereas rules with many COMPARISONS also have more ELIMINATIONS. To minimize these intercorrelation problems, we repeated the random selection procedure 1,000 times and selected the set of 120 decision problems with the smallest intercorrelations. The resulting intercorrelations are shown in Table 3. Despite these efforts, we were unable to further reduce the highest, COMPARES and ELIMINATIONS, for the reasons outlined above.

The Computer-Based Information Acquisition System

A computer-based information acquisition system called MOUSELAB was utilized in carrying out the experiment (Johnson, Payne, Schkade, & Bettman, 1986). The subject saw a matrix display on the computer monitor for each

Table 3

Intercorrelations Among EIP Counts for the 120 Decision Problems Selected

	Operators				
	ADDITIONS	PRODUCTS	COMPARES	ELIMINATIONS	DIFFERENCES
READS	.487	.543	.541	.280	.272
ADDITIONS		.591	-.259	-.495	.140
PRODUCTS			-.302	-.374	-.146
COMPARES				.852	.492
ELIMINATIONS					.158

decision problem. The rows of the matrix were labeled weights, cutoffs, and then the names of the alternatives to be considered. The columns were labeled with the names of the attributes. At the bottom of the monitor screen were boxes used to indicate choice of an alternative (hence termed choice boxes). For an example of this display, see Figure 1.

Initially, the matrix display provides only the labels for the rows and columns and the choice boxes. The information is hidden in the blank cells on the screen. To acquire information, the subject must move a cursor controlled by the mouse to the desired cell of the matrix. The cell then opens, displaying the information. For each decision, the subject would use the mouse to acquire the appropriate information in the sequence specified by the current strategy. MOUSELAB recorded the sequence in which cells were opened and the time spent in each cell. The time measurements use the system clock of the personal computer, providing a resolution of approximately 17 milliseconds. After the requisite

information had been examined, the subject moved to the appropriate choice box and clicked a button on the mouse to designate the chosen alternative.

A crucial feature of MOUSELAB for the present study is the ability to monitor the sequence of acquisitions made by a subject. Since the EIP models of effort we propose require EIP counts for each problem, it is crucial that subjects use the strategy exactly as it is specified, so that the EIP counts can be predicted accurately. For example, to ensure that the EIP counts for the weighted adding and EBA examples given above are correct, we must monitor that subjects follow the exact acquisition sequence for each rule. MOUSELAB includes a move monitoring feature, which allows the correct sequence of cells to be specified for each decision problem. If the subject enters a "wrong" cell, the cell will not open, and after two seconds the computer will emit an audible buzz. The attempt to enter an incorrect cell is also recorded in the output information about the subject's move sequence. Hence, trials where a specified number of incorrect moves has occurred can later be discarded or analyzed as error trials if desired.

An analysis of a typical decision task for this study using Fitts Law (Card, Moran, & Newell, 1983) indicates that subjects could move between information cells in less than 100 milliseconds. This suggests that the time to move the mouse is limited mainly by the time it takes to think where to point, not the movement of the mouse itself.

Procedure

Overview. Subjects participated in eight separate sessions over a period of several days. Each session lasted from one to one and a half hours. No more than two sessions were run in one day, and separate sessions were at least four hours apart. The first session taught subjects the decision rules and

familiarized them with MOUSELAB. In each of the subsequent six estimation sessions, a subject made twenty choices using a different specified rule. The order of the rules was randomized across subjects. The final session had twelve choice problems where the subject was free to use any strategy desired. These problems all had four attributes and a third of the problems had two, four, and six alternatives, respectively.

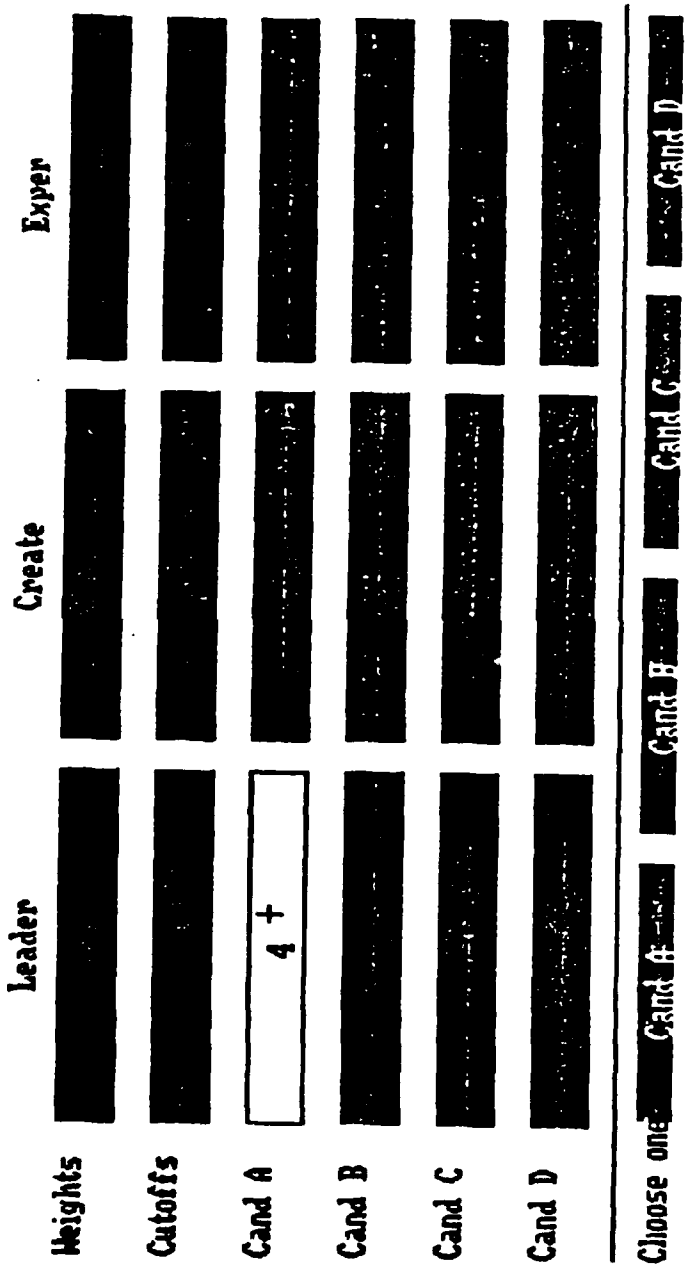
Subjects. Subjects were seven adults, ranging in age from 21 to 34, and included four males and three females. They varied in their prior awareness of the decision making literature, ranging from graduate students who had studied decision making to non-students who had never been exposed to those concepts.

Training. It was crucial that subjects thoroughly learn the six decision strategies to be used (weighted adding, equal-weighted adding, lexicographic, elimination by aspects, satisficing, and majority of confirming dimensions) and learn to use MOUSELAB. Hence, a familiarization session was developed. Subjects were first introduced to the mouse and were shown how to use it to open the cells, respond to various response scales, and indicate a choice. After practicing these tasks, subjects were next given a training session for the decision rules which was developed using the MOUSELAB system.

The subject was informed that the decisions to be made were personnel decisions involving selection of job candidates. These selections were to be made according to the rules specified by different divisions of their company, and the sets of candidates might have both differing numbers of candidates (from two to six) and different amounts of information on each candidate (from two to four attributes). The four possible attributes were leadership potential, creativity, job experience, and motivation. The left to right ordering of the subset of these attributes used on any given trial was randomized.

Figure 1

Example of A Stimulus Display Using Mouselab System



Next, subjects were introduced to the ratings used to describe each candidate on each attribute. Ratings ranging from 2 (poor) to 7 (excellent) were used as the information in each cell. Subjects were then introduced to the ideas of importance weights for the attributes and cutoffs for the attributes. They were then asked to select the most important attribute and to pick candidates surpassing a cutoff to provide training using these ideas. These concepts were then reviewed before the decision rules were introduced.

For each rule, the subject was first given a thorough written description of the rule on the computer monitor. Then the subject was given several decision problems and told to apply the rule using the mouse. The move monitoring system was used on the last trial to inform subjects of mistakes. The subject was also told what the correct choice using the rule should have been. Thus, subjects had accuracy feedback on both the sequence of acquisitions and their choices during training. Following these practice trials, the next rule was presented. The rules were presented in the familiarization session in an order ranging from simple to more complex: equal-weighted adding, lexicographic, satisficing, elimination by aspects, weighted adding, and majority of confirming dimensions.

Finally, after all six rules had been presented, subjects were given six practice trials, one for each rule. These trials introduced the use of two response scales to measure the difficulty of the decision task and how effortful the decision was. The first scale asked the subject to rate how difficult the choice was to make on a scale ranging from 0 (not difficult at all) to 10 (extremely difficult). The second scale asked the subject to rate how much effort he or she put into making the choice on a scale ranging from 0 (hardly any effort) to 10 (a great deal of effort). The purpose of these six practice trials was threefold: 1) to introduce the response scale; 2) to consolidate the learning of the rules; and 3) to introduce subjects to the range of difficulty in

the problems so that they could calibrate their use of the response scales more accurately during the actual estimation sessions. This latter purpose was accomplished by selecting a variety of problem sizes and difficulty levels for the six practice trials.

Estimation Sessions. At the beginning of each session, the subject was given a review of that session's decision rule. The rule was described again, and several practice trials were given, with feedback on the accuracy of the acquisition sequence and choice. Then subjects were given a sequence of decision problems where they had to make two consecutive choices using the rule with no errors in acquisition sequence or alternative chosen. Following successful completion of these trials to criterion, the actual experimental trials for that session began.

As noted above, the twenty choice problems for each decision rule were presented to the subject on an IBM Personal Computer via the MOUSELAB software. Subjects used a Mouse Systems mouse as a pointing device. These problems were randomly ordered (the random order was the same for all subjects). For each problem, the subject followed the sequence of acquisitions implied by the rule. The move monitoring system described above was used to monitor subjects' adherence to the correct sequence for the rule. Subjects then indicated the alternative chosen, and responded to the difficulty and effort scales described above. For each choice, MOUSELAB recorded the sequence of acquisitions, the time of entry and exit for each cell, the alternative chosen, and values on the two response scales. The overall latencies for the choice and the two scale responses were also recorded.

After completing all eight sessions, subjects received $40 for their participation. In addition, they were told that three $5 bonuses would be paid

for (1) above average performance in terms of overall accuracy, (2) minimization of incorrect search, and (3) speed of decision, respectively. In other words, subjects were informed that they could earn an additional payment of up to $15 dollars depending upon their performance.

Preliminary Analyses

Before the major analyses could be performed, the data were analyzed to determine the prevalence of errors, the existence of speed-accuracy tradeoffs, and the relationship between the two self-report measures of effort.

Subjects selected incorrect alternatives on 11.4% of the trials. In addition, .8% of the trials contained severe deviations from the correct sequence of acquisitions specified for that trial (i.e., more than two "buzzes"), even though the correct alternative was still selected. Taken together, this yields a total of 12.2% error trials. Over half of these errors come from the weighted adding (27.1%) and elimination by aspects (32.2%) rules. For all analyses, all error trials of both types were removed from the data. However, analyses performed when all trials were included show virtually identical results.

To examine the possible existence of speed-accuracy tradeoffs, response latency was correlated with error, both across and within strategies. Overall, the correlation between time for each decision and the probability of an error was .15 ($p<.0001$). Similar positive correlations were obtained for each rule, subject, and rule by subject combination. In no case was there a significant negative correlation, which indicated that these data are relatively free from any concerns with speed-accuracy tradeoffs.

Finally, the two self-report measures of effort and difficulty were examined. Their intercorrelation was .85, suggesting that they measure the same

underlying construct. A principal components analysis showed that the first factor accounted for 93% of the variance in the scores, so the two ratings were added to form an overall index of subjective effort.

For the analyses we report, the various models described below are estimated using different independent variables. In every model, however, dummy variables representing the subject and session (i.e., the order of that session among the six estimation sessions) are included, as are variables representing the linear and quadratic effects of trial (i.e., the order among the twenty decision problems within any session). These variables, although statistically significant, account for small portions of the explained variance and simply allow for changes in the intercept term across sessions and subjects and for any effects of practice across trials to be taken into account. Since the effects are not theoretically important for our purposes, they are not reported in the discussion of the results.

Overview of the Analyses

As discussed above, we consider two major indicators of strategy execution effort for the experimental data collected: response times and an index of self-reported effort. In the results section below, we first present data showing the average performance across subjects on these two measures for the various rules for the different problem sizes.

Following this attempt to characterize strategy performance, we examine the two classes of models for effort we outlined above: behavioral (informational) and EIP. Recall that the behavioral model attempts to explain effort using the only overtly observable behavior, the number of information acquisitions (READS). Four different EIP models are also examined. In the equal-weighted EIP model, all EIPs are given the same weight. In contrast, the weighted EIP model allows each EIP to have its own characteristic effect upon each dependent measure. The

third model, the weighted EIP by rule model, allows the effect of each EIP to vary by rule. Finally, the weighted EIP by individual model allows the coefficient of each EIP to vary by individual. Note that allowing the coefficients to vary across individuals is what characterizes this model; individual subject dummy variables which allow the intercept term to vary over individuals are included in all of the models, as are the session and trial variables described above. Regression analyses are performed using the independent variables specified by each model and response latency and self-reported effort as dependent variables. We can assess the relative fit for each model and test the significance of certain model comparisons.[1]

Results

Before considering the fit of the various models, we first present the average response times and self-reported effort levels for the various rules for each problem size. Then we consider the models of response times and self-reports of effort, respectively.

Average Response Times and Self-Reports of Effort by Strategy and Problem Size

Table 4 summarizes the average response times, and Table 5 presents the self-reports of effort for each decision strategy for the different problem sizes. These data are averaged across all seven subjects. Recall that some problem sizes were not used for some strategies because of the selection procedure described above.

As would be expected, decision problems of increasing complexity, i.e., more alternatives and/or more attributes, take longer and are viewed as more effortful. An analysis of variance of response times showed both a main effect of number of alternatives ($F(4,647) = 46.21$, $p < .0001$; means of 17.2, 22.5, 26.3, 36.4, and 57.8 seconds for 2,3,4,5, and 6 alternatives respectively) and

number of attributes ($F(2,647) = 52.36$, $p < .0001$; means of 22.0, 29.3, and 41.0 seconds for 2,3, and 4 attributes, respectively). Similarly, for self-reports of effort there were main effects for both number of alternatives ($F(4,647) = 26.52$, $p < .0001$; means of 2.7, 3.5, 4.2, 5.3, and 6.1 for 2,3,4,5, and 6 alternatives, respectively) and number of attributes ($F(2,647) = 33.19$, $p < .0001$; means of 3.5, 4.1, and 5.5 for 2,3, and 4 attributes, respectively).

Of perhaps greater interest, the effects of task complexity vary by strategy. For response time, there were significant rule by number of alternatives ($F(20,647) = 8.78$, $p < .0001$) and rule by number of attributes ($F(10,647) = 3.38$, $p < .0005$) interactions, and a marginally significant rule by number of alternatives by number of attributes interaction ($F(30,647) = 1.46$, $p < .06$). For the self-reports of effort, there was a significant rule by number of alternatives interaction ($F(20,647) = 1.98$, $p < .007$), a marginally significant rule by number of attributes interaction ($F(10,647) = 1.77$, $p < .07$), and a non-significant three-way interaction ($F(30,647) = .43$, ns). The form of these interactions is that the weighted additive rule shows much more rapid increases in response time and generally shows more rapid increases in self-reports of effort as a function of increases in task complexity than the other strategies. This is of course consistent with a great deal of other research showing that individuals shift toward simplifying decision heusistics as a function of increases in task complexity, particularly with increases in number of alternatives (Payne, 1982).

Table 4

Average Response Times by Strategy and Problem Size

Strategy							
Problem Size							
Number of Alternatives	Number of Attributes	WADD	EQW	LEX	EBA	SAT	MCD
	2	18.4[a]	12.7	8.7	--[b]	8.5	--
2	3	24.6	11.5	12.5	15.7	12.8	18.2
	4	33.0	15.8	17.7	--	23.9	24.9
	2	35.0	26.8	17.0	11.9	--	17.8
3	3	41.6	18.3	16.4	17.2	16.5	22.1
	4	64.6	21.5	21.5	--	27.8	38.4
	2	39.4	21.3	12.6	14.3	13.8	16.7
4	3	47.8	29.7	18.7	17.6	22.3	32.2
	4	77.5	40.5	26.9	26.1	24.2	--
	2	46.7	29.0	15.0	19.5	--	--
5	3	76.6	46.3	26.2	14.4	30.4	33.1
	4	86.7	42.2	36.0	36.4	36.8	47.1
	2	62.7	39.0	20.0	--	--	28.7
6	3	162.4	48.3	31.7	18.5	41.6	32.5
	4	154.5	71.7	46.7	31.0	62.5	46.9

[a] Average response time, in seconds

[b] This problem size not selected for this rule.

Table 5

Average Self-Reports of Effort by Strategy and Problem Size

Strategy							
Problem Size							
Number of Alternatives	Number of Attributes	WADD	EQW	LEX	EBA	SAT	MCD
	2	3.77[a]	2.56	.93	--[b]	1.73	--
2	3	3.81	1.67	1.4	2.43	1.79	2.57
	4	6.90	2.34	3.33	--	1.74	4.48
	2	4.91	3.40	1.83	2.49	--	3.92
3	3	5.73	2.78	2.97	3.48	3.34	4.47
	4	5.67	3.45	2.65	--	3.67	5.46
	2	6.85	3.23	2.45	2.62	2.37	4.58
4	3	7.63	3.01	3.20	3.37	3.72	4.70
	4	8.61	6.35	4.49	5.15	4.08	--
	2	7.08	3.73	2.94	2.90	--	--
5	3	6.37	4.07	4.73	2.87	5.50	6.74
	4	10.29	5.71	5.20	6.22	5.35	7.22
	2	6.88	4.76	2.13	--	--	5.02
6	3	8.92	5.40	5.03	2.52	6.59	6.33
	4	11.0	9.72	6.22	5.40	7.24	6.00

[a] Average self-reported effort, on a 0(low) to 10(high) scale

[b] This problem size not selected for this rule.

The results presented above and in Tables 4 and 5 demonstrate that the various rules perform differently in different task environments in terms of two indicators of effort, response time and self-reports of effort. The central question of interest, however, is whether the componential framework proposed above can provide a unifying treatment of the effort required by these rules and model these differences in effort. Hence, we examine the extent to which the various models outlined above fit the data summarized in Tables 4 and 5. We explore that issue for response time and self-reports of effort in turn.

Analysis of Response Times

Table 6 provides a summary of the degrees of fit for the four EIP models and the behavioral model (reads only).[2] All the models provide good fits for the overall response times ($p < .0001$). Note that the fit of the weighted EIP model is significantly better than that of the behavioral model ($F(5,713) = 81.4$, $p < .0001$) or that of the equal-weight EIP model ($F(5, 713) = 78.9$, $p < .0001$).[3] Thus, it appears that a model of cognitive effort in choice, as measured by response time, requires concern not only for the amount of information processed (READS), but also the various processes applied to that information (e.g., Products and Comparisons), with differential weighting of those operators.

Table 6

Degree of Fit for Models of Response Time and Self-Reports of Effort

R^2 Values

Model	Response Time	Self-Reports of Effort
Behavioral	.75	.56
Equal-weighted EIP	.75	.55
Weighted EIP	.84	.59
Weighted EIP by Rule	.84	.61
Weighted EIP by Individual	.90	.80

While the degree of fit for the weighted EIP model is impressive, we must examine whether more complex models improve the fit. First, we consider the weighted EIP by rule model, which allows the time for each EIP to vary by rule, to determine whether the EIPs require the same time for each rule. The weighted EIP model is a special case of the weighted EIP by rule model, so the significance of the incremental fit can be tested. The incremental fit is not significant ($F(13, 700) = 1.37$, ns); hence, the assumption that each operation requires a constant amount of time independent of the strategy in which it is used seems reasonable.

The weighted EIP by individual model allows the times for the EIPs to vary across subjects. Even if individuals use the same strategy, they may differ in the amount of time required for each component process (Hunt, 1978; R. Sternberg, 1977). This model achieves an $R^2 = .90$, with significantly better fit than the weighted EIP model (Incremental $R^2 = .06$, $F(36, 677) = 10.9$, $p < .0001$). These individual differences are considered further in the discussion section.

Thus, based upon the analyses of response times, the weighted EIP model, and hence the EIP conceptualization of decision effort, receives strong support. The EIP times appear to vary across individuals, although not across rules.[4]

These results also hold up well in cross-validation. Estimating the model on one-half of the data and using these estimates to predict the other half yields average R^2 values of .74, .73, .81, .82, and .88 for the behavioral, equal-weighted EIP, weighted EIP, weighted EIP by rule, and weighted EIP by individual models, respectively.

Estimates of EIP Times. Since the weighted EIP model received strong support, estimates of the times for each operator are shown in Table 7. Although the estimates vary to some extent across individuals, as a first approximation we consider the pooled results.

Table 7

Coefficient Estimates of Response Time and Self-Reports of Effort for EIP's

EIP	READS	ADDITIONS	PRODUCTS	COMPARISONS	ELIMINATIONS	DIFFERENCES
Response Time	1.19*	.84*	2.23*	.09	1.80*	.32
Self-Reports of Effort	.10*	.08*	.19*	.04	.32*	-.12

*Significantly different from zero at $p < .05$.

The coefficients are all positive, with most significantly different from zero. The estimates also tend to agree with estimates for similar EIPs provided by other studies. The READ EIP combines encoding information with the motor activity of moving the mouse. Its estimated latency is 1.19 seconds ($t(713) = 6.55$, $p < .0001$). This estimate is plausible, since it might consist of the movement of the mouse, estimated to be in the range of .2 - .8 seconds by Johnson, Payne, Schkade, and Bettman (1986), and an eye fixation, estimated to require a minimum of .2 seconds (Russo, 1978). ADDITIONS and SUBTRACTIONS both take less than one second, with estimates of .84 ($t(713) = 4.54$, $p < .0001$) and .32 ($t(713) = .98$, n.s.) respectively. These values are not significantly different ($t(713) = 1.03$, n.s.) and are consistent with those provided by Dansereau (1969), Groen and Parkman (1972), and others (see Chase, 1978, Table 3, p. 76). Our estimate for the PRODUCT EIP, 2.23 seconds ($t(713) = 10.36$, $p < .0001$), is larger than that commonly reported in the literature.

The time for COMPARISONS is very short, .08 seconds ($t(713) = .22$, n.s.), and that for ELIMINATIONS, 1.80 seconds ($t(713) = 3.00$, $p < .01$), is relatively long. This may reflect the collinearity of COMPARES and ELIMINATIONS.

In sum, based both upon its degree of fit and the generally plausible time estimates for the EIPs, the proposed weighted EIP model receives impressive support when response times are used as an indicator of effort. The next set of results examines the performance of the various models when self-reports of effort form the indicator of effort.

Analysis of Self-Reports of Effort

There are several reasons why self-reports of effort are interesting as a second indicator of decision effort. First, self-reported effort might tap different aspects of strategy execution effort and might not be closely related to decision latency. As Kahneman (1973) observed, two different mental tasks may take similar amounts of time, but one might be seen as much more effortful than the other. This speculation receives some support in our data: the overall correlation between time and the self-reported effort index is .29. Secondly, while the analysis of latency helps validate the proposed EIP conceptualization of effort, self-perceptions of effort may also be important in understanding why decision-makers avoid certain strategies. However, several cogent arguments for caution in the use of self-reported measures of effort should also be noted. Foremost among these is the possibility that subjects cannot accurately report demands on cognitive resources (Gopher and Donchin, In press), or that such reports do not allow comparisons across tasks which make widely differing demands.[5]

Model Fit. From the results shown in Table 6, it can be seen that the absolute levels of fit are lower than for the response latencies, but are still highly significant ($p < .0001$).[6] The weighted EIP model again provides significantly greater fit than the behavioral ($F(5, 713) = 10.0$, $p < .0001$) or equal-weighted EIP ($F(5, 713) = 13.0$, $p < .0001$) models.

The weighted EIP model of subjective effort can also be compared to more complex models. The weighted EIP by rule model shows a small, but statistically significant increase in fit (incremental $R^2 = .02$, $F(13,700) = 2.6$, $p < .002$). The weighted EIP by individual model shows a substantial increase in fit (incremental $R^2 = .21$, $F(36,677) = 20.1$, $p < .0001$).

Hence, the results essentially replicate those for response times. The weighted EIP model provides the best explanation of decision-makers' self reports of the effort associated with each decision problem, and the effort estimates appear to vary across individuals, but only slightly across rules.

Cross-validation of these results is also encouraging. Average R^2 values of .53, .54, .58, .60, and .78 are obtained for the behavioral, equal-weighted EIP, weighted EIP, weighted EIP by rule, and weighted EIP by individual models, respectively.[7]

Estimates of EIP Effort. Estimates of the subjective effort associated with each EIP from the weighted EIP model pooled across subjects are given in Table 7. These estimates represent the increase in reported effort per EIP on the sum of two 0-10 scales. The largest estimate is for the ELIMINATION operator, .32. However, the high intercorrelation between ELIMINATIONS and COMPARISONS (.85) must temper any interpretation of this coefficient and the small (.04) coefficient for COMPARISONS. The PRODUCT operator, as might be expected, is seen as fairly effortful, with a coefficient of .19, while the coefficients for READS and ADDITIONS are also significantly positive.[8]

Discussion

The concept of effort plays a major role in attempts to understand the contingent use of processing strategies. An approach to measuring the effort associated with different decision strategies is proposed in this study, using a set of elementary operators (i.e., READS, ADDITIONS, COMPARISONS, PRODUCTS,

DIFFERENCES, and ELIMINATIONS) as a common "language" for describing decision strategies. This set of operators is used to generate a metric of the effort required to execute a decision strategy in terms of the number of EIPs involved.

The empirical results yielded strong support for this proposed componential approach to strategy effort. A model of effort based upon weighted EIP counts (the weighted EIP model) provided good fits for response times and self-reports of effort, two different measures of decision effort. In addition to this absolute level of fit, the weighted EIP model also was statistically superior to a behavioral model using only reads and to an equal-weight EIP model for each of the two indicators of effort.

The estimates of time taken for each EIP were mostly plausible and in line with prior research, hence providing additional confidence in the approach. We also examined the potential generalizability of our results to a broader range of cognitive tasks. Specifically, *estimates* of the times taken for various EIPs drawn from studies of other information processing tasks (see Johnson and Payne, 1985, p. 406 for the specific values of these estimates) were used as weights to produce an analogue to the weighted EIP model for response times.[9] That is, the values drawn from the literature for the time for each EIP were used as coefficients of the EIP counts to produce a predicted response time. This model produced an R^2 value of .81, only slightly below that of the weighted EIP model. The performance of this model provides encouraging evidence that the componential approach may generalize to a variety of cognitive tasks. In addition, the closeness of the time estimates for individual EIPs obtained from our study of decision making to those derived from other cognitive tasks, noted above, provides support for the generalizability of our experimental procedure.

In general, the weights for various EIPs obtained in our study were essentially the same regardless of the decision strategy used. Hence, the

original assumptions of serial processing and independence of EIP duration across rules and problem sizes made by Johnson and Payne (1985) receive encouraging support in this research. Taken together, these results imply that a small number of simple operators can be viewed as the fundamental components from which decision rules are constructed (Bettman, 1979; Bettman and Park, 1980).

However, the results do suggest significant individual differences in the effort associated with individual EIPs. For example, for some individuals computational operators were relatively more difficult than comparisons. For others, this difference was not present. This suggests the possibility that individuals may choose different rules in part because different component EIPs may be relatively more or less difficult or effortful across individuals. In addition, although the evidence for a model of effort based upon EIP counts is impressive, the findings presented thus far are all limited to a situation in which individuals were required to use various strategies which had been prescribed for them. Suppose, however, that parameters characterizing individual subjects' performance on this constrained choice task (e.g., average EIP times) could be related to those subjects' behaviors in a choice task where subjects were free to use whatever strategy they wished. This would provide suggestive evidence for the proposed componential approach.

As an exploratory analysis, we related the average times spent by subjects on arithmetic operations (ADDITIONS and PRODUCTS) in the constrained choice tasks to the processing patterns used by those subjects in the unconstrained choices they made in the final experimental session. In particular, processing patterns of three subjects for whom arithmetic operators were relatively more expensive (took more time) were compared to those of the four subjects for whom such operators took less time. The subjects for whom the arithmetic operators were relatively more expensive showed significantly greater variability in their

information acquisition across attributes and alternatives on the twelve unconstrained choices. This result is consistent with use of more heuristic, non-compensatory processes rather than use of computationally expensive compensatory strategies such as weighted adding (Payne, 1976). Showing that performance on the constrained task can be related to processing in unconstrained choice situations offers suggestive support for the EIP approach, although the small sample size precludes strong conclusions.

Another contribution of the study is more methodological. The MOUSELAB decision-monitoring software and hardware worked exceptionally well in providing detailed data about the decision task. The ability to monitor the sequence of acquisitions, measure latencies, and in general maintain experimental control over the choice task makes this system potentially very valuable for a variety of research issues in decision making and other areas of cognition.

The attainment of experimental control, necessary to predict the operators used and implement the proposed EIP models of effort, is not without costs. In the constrained decision task, subjects do not select strategies; rather, they apply given rules. Hence, the task eliminates many difficult problems normally faced by individuals making decisions. Subjects did not have to select or construct a strategy, and the sequence of operations was specified. Thus, they did not have to engage in possibly effortful control processes determining what to do next. In addition, by providing all of the weights, cutoffs, and ratings, the need for potentially difficult valuation processes was eliminated. Finally, some of the timing estimates are undoubtedly affected by the specific apparatus used (i.e., the matrix display and the mouse). These restrictions may be less worrisome, however, given the analyses of the "free choice" task. Since the timing estimates derived from the constrained choices predict aspects of the processing patterns in the free choices, our confidence in the procedures used is

increased. However, further research relaxing these restrictions on processing flexibility would be desirable.

A second set of caveats is that although an approach which breaks down decision strategies into more detailed components seems to be strongly supported as an approach to measuring decision effort, we have focused on a particular level of detail in taking such an approach. For example, one could model multiplications in terms of underlying arithmetic operations (e.g., Dansereau, 1969) or anchoring and adjustment (Lopes, 1982). In addition, one could extend our models to include EIPs that model the transfer of information to long-term memory and various mental "bookkeeping" operations.

Modeling cognitive effort at the level of EIPs allows us to examine how the effort associated with various strategies might vary as a function of differences in task environments. In particular, such variation in effort across task environments could be predicted by computer simulation of the performance of different heuristics in such environments. As an example of this approach, Payne, Bettman, and Johnson (In press) used both computer simulation and process tracing experiments to examine the joint effects of effort and accuracy in the adaptive use of decision processes. A Monte-Carlo simulation study utilized the proposed measure of effort based on EIP counts, along with various measures of accuracy, to identify heuristic choice strategies that approximated the accuracy of normative procedures and required substantially less effort. No single heuristic, however, did well across all task environments. Thus, a decision maker striving to maintain a high level of accuracy with a minimum of effort would have to use a variety of heuristics.

Payne, Bettman, and Johnson (In press) then tested the degree of correspondence between the efficient processing strategies for a given decision problem identified by the simulations and the actual information processing

behavior exhibited by people. People were shown to be highly adaptive in their responses to changes in the nature of the alternatives available to them, and to the presence or absence of time pressure. The results for actual decision behavior tended to validate the patterns expected on the basis of the simulation estimates. Of particular interest was the finding that people were sensitive to changes in decision context that impact the relative accuracy of heuristics as well as affecting relative effort.

Taken together, the present results, plus those reported in Payne, Bettman, and Johnson (In press), support the hypothesis that decision-makers choose strategies as a function of a strategy's demand for mental resources, i.e., the effort required to use a strategy, and the strategy's ability to produce an accurate response. However, it is important to recognize that a cost/benefit viewpoint of strategy selection does not rule out the possibility of other factors impacting strategy usage. For example, there is growing evidence that justifiability may influence the choice of processing strategy (e.g., Tetlock & Kim, 1987). In addition, more perceptual factors such as the decision frame (Tversky & Kahneman, 1981) may also influence strategy use. Nonetheless, the present study, along with others, shows how measures of decision effort can be predictive of strategy use.

Finally, the approach to measuring cognitive effort developed in this paper may also have applied value. For example, recently it has been suggested that the use of nutritional information in the supermarket by consumers might be improved by decreasing the effort costs associated with processing that information (Russo, Staelin, Nolan, Russell, and Metcalf, 1986). The methodology developed in this paper could be used to test the impact of different information displays on the use of a preferred decision strategy. A related area of

application would be the design of computer-based decision aids (Keen & Scott-Morton, 1978; Kleinmuntz & Schkade, 1988).

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Authors' Notes

The research reported in this paper was supported by a contract from the Engineering Psychology Program of the Office of Naval Research. The order of authorship is arbitrary. Each author contributed equally to all phases of this project. Requests for reprints should be sent to James R. Bettman, Center for Decision Studies, Fuqua School of Business, Duke University, Durham, North Carolina 27706.

Footnotes

[1]The behavioral model and the equal-weight EIP model are special cases of (or nested within) the weighted EIP model. Hence, the additional fit provided by the weighted EIP model over each of these two simpler models can be tested statistically (Neter and Wasserman, 1974, p. 89). Similarly, the weighted EIP model is nested within the weighted EIP by rule and weighted EIP by individual models.

[2]Although not the subject of interest in this paper, for completeness a model using as independent variables the number of alternatives, the number of attributes, their product, and a dummy variable for each rule was estimated. The R^2 values for response time and self-reported effort were .65 and .57, respectively.

[3]The degrees of freedom for the numerator in these comparisons represent the difference between the use of six EIP variables for the weighted EIP model and one variable for the behavioral and equal-weight EIP models. The degrees of freedom for the denominator reflect the total trials and the total number of variables used for the weighted EIP model (Neter and Wasserman, 1974, p. 89).

[4]The models were also estimated using the response time data disaggregated to the level of individual acquisitions, the total time spent on each alternative, and the total time spent on each attribute. The relative fits of the various models essentially replicate those of the aggregate results, although the absolute levels of fit are of course lower for the more disaggregate analyses.

[5]There may be a distinction between anticipated effort and experienced effort, with the former being the effort a strategy is predicted to require for solving a problem and the latter reflecting the effort actually used. In the current study, we focus on experienced effort. While strategy selection may be a function of anticipated effort, we argue that a major basis for estimating

function of anticipated effort, we argue that a major basis for estimating anticipated effort is experienced effort on previous decision tasks. Hence, analysis of experienced effort can potentially lead to insights into the bases for anticipated effort. The relationship between anticipated and experienced effort is an important topic for study, but it is beyond the scope of the current investigation.

[6]If we assume that the two self-report measures of effort and difficulty which we combined to form the self-reported effort index are both fallible measures of effort, the intercorrelation between them (r=.85) serves as a baseline to assess the reliability of this index. Correcting for this unreliability would provide an estimated R^2 of .83 for the weighted EIP model for effort (Ghiselli, Campbell, and Zedeck, 1981, p. 290.)

[7]To further explore the robustness of the results, models for both response times and self-reports of effort were run which added variables for the number of alternatives, the number of attributes, and dummy variables for rules to the weighted EIP by individual model. While these additional variables produced significant increases in fit ($F(11,666) = 3.30$, $p < .0002$ and $F(11,666) = 4.04$, $p < .0001$ for response time and effort respectively), the increases in R^2 are very small (.005 and .012 for response time and effort, respectively).

[8]Although errors are only indirectly related to decision effort, for the sake of completeness logistic regressions were run using the behavioral, equal-weighted EIP, and weighted EIP models with a 0-1 dependent variable representing whether or not an error was made on a particular choice problem. The pseudo-R^2 values from this analysis were .62, .63, and .64 for the behavioral, equal-weighted EIP, and weighted EIP models, respectively. The weighted EIP model performed better than the behavioral model ($p < .05$) but not better than the equal-weighted EIP model ($p = .105$).

[9]The weighted EIP model for times was the only model considered, since the

[9]The weighted EIP model for times was the only model considered, since the estimates from the literature only refer to times and do not account for individual differences or differences across rules.